Risk factors for 30-day hospital readmission in patients ≥65 years of age

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The objective of the study was to develop and validate predictors of 30-day hospital readmission using readily available administrative data and to compare prediction models that use alternate comorbidity classifications. A retrospective cohort study was designed; the models were developed in a two-thirds random sample and validated in the remaining one-third sample. The study cohort consisted of 29,292 adults aged 65 or older who were admitted from July 2002 to June 2004 to any of seven acute care hospitals in the Dallas–Fort Worth metropolitan area affiliated with the Baylor Health Care System. Demographic variables (age, sex, race), health system variables (insurance, discharge location, medical vs surgical service), comorbidity (classified by the Elixhauser classification or the High-Risk Diagnoses in the Elderly Scale), and geographic variables (distance from patient's residence to hospital and median income) were assessed by estimating relative risk and risk difference for 30-day readmission. Population-attributable risk was calculated. Results showed that age 75 or older, male sex, African American race, medical vs surgical service, Medicare with no other insurance, discharge to a skilled nursing facility, and specific comorbidities predicted 30-day readmission. Models with demographic, health system, and either comorbidity classification covariates performed similarly, with modest discrimination (C statistic, 0.65) and acceptable calibration (Hosmer-Lemeshow χ^2 = 6.08; $P >$ 0.24). Models with demographic variables, health system variables, and number of comorbid conditions also performed adequately. Discharge to long-term care (relative risk, 1.94; 95% confidence interval, 1.80–2.09) had the highest population-attributable risk of 30-day readmission (12.86%). A 25% threshold of predicted probability of 30-day readmission identified 4.1% of patients ≥65 years old as priority patients for improved discharge planning. We conclude that elders with a high risk of 30-day hospital readmission can be identified early in their hospital course.

In 2003 there were 13.2 million hospital admissions among 35.4 million US adults aged 65 or older (here called *elders*) (1, 2). Overall, 18% of elders had one or more admissions. Many elders admitted to acute hospital care have multiple admissions (3–6). A hospital readmission may result from a new condition, a recurrent exacerbation of a known chronic condition, a complication resulting from previous medical or surgical care, adverse drug events and injuries associated with or as a consequence of health care (7), or premature discharge to a setting where patient needs for posthospital care are not met (8).

Studies of risk factors for hospital readmission in elders have identified patient characteristics, disease characteristics, and health care system factors that predict hospital admission or readmission (4, 9–12). Comorbidity measures using readily available hospital administrative data have been used to predict hospital mortality, length of stay, charges (13–15), and postdischarge mortality (13, 16). Some studies have used readily available administrative data (3–4), while others have used clinical data directly collected from patients or from patients' hospital records (9–11). Hospital discharge data have been used to identify factors associated with hospital readmission, but these analyses have been designed primarily to assess quality of hospital care (4, 8, 17–19).

Coleman identified problems in the postdischarge period and the need for improved discharge planning, an approach that has been termed "transitional care" (20–23). An essential requirement for hospital transitional care programs is the early identification of currently hospitalized patients who have an increased risk of future readmission. The aims of this study were to develop and validate a prediction model using hospital administrative data that could easily be adapted for use in discharge planning to predict elders' risk of future hospital readmission.

METHODS

Study setting, design, and patient population

This retrospective cohort study was conducted at the seven acute care hospitals of the Baylor Health Care System (BHCS) located in the 12-county Dallas–Fort Worth metropolitan area (Census 2000 population estimate, 5,221,801). The study hospitals were Baylor University Medical Center at Dallas (997 beds), Baylor All Saints Medical Center at Fort Worth (529 beds), Baylor Medical Center at Irving (288 beds), Baylor Medical Center at Garland (220 beds), Baylor Regional Medical Center at Grapevine (197 beds), Baylor Medical Center at

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Southwest Fort Worth (71 beds), and Baylor Medical Center at Waxahachie (69 beds).

Adults aged 65 or older who were admitted from July 2002 through June 2004 were eligible for the study. Information was obtained from the BHCS electronic data warehouse, an administrative data source for all hospital discharges from the BHCS hospitals. Patients were identified by Social Security number. Within the 2-year study period there were 56,670 hospital encounters for 35,804 unique patients who were alive at discharge. Hospital encounters for day surgery, dialysis, transfusions, or other ambulatory services that did not meet criteria for a hospital admission were excluded (N = 5145). Transfers to another acute care hospital, rehabilitation hospital, or hospice (N = 993) were excluded because the patients' risk of readmission would be confounded by their subsequent care. Patients admitted to the psychiatric service (N = 126) were also excluded because their discharge planning and postdischarge care patterns differed from those admitted to the medical or surgical services. Elders admitted and discharged on the same day were excluded (N = 245), as were those whose admission data lacked a diagnosis-related group (DRG) (N = 2) or payer type (N = 1). The 44 patients who left against medical advice were not excluded from the analysis. Our final analysis cohort included 29,292 patients. All patient identifiers were removed from the analytic data set. The study was approved by the BHCS institutional review board.

Outcomes and independent variables

The primary outcome of interest was readmission to any of the seven BHCS hospitals within 30 days of discharge of the patient's first admission to a BHCS acute care hospital inpatient medical or surgical service during the study period. Four classes of independent variables were analyzed: demographic, health system, comorbidity, and geographic. Demographic variables were age, sex, and race/ethnicity. Prior to July 2005, race and ethnicity data were not reliably collected at each hospital; therefore, race/ethnicity was classified as white, black, or other for these analyses. The "other" category included 49.7% Hispanic ethnicity without classification as white or nonwhite and 8.3% Asian race.

The health system variables were health insurance, hospital service, and discharge location. Health insurance was coded as Medicare only, Medicare and other supplemental insurance, Medicare and Medicaid with or without other supplemental insurance, and other insurance without Medicare. Hospital service was dichotomized into medicine or surgery, and discharge location was categorized as home, home with home care, or skilled nursing facility. Comorbidity was based on either the most recent version of the Elixhauser classification (15), distributed by the Agency for Healthcare Research and Quality, or the recently developed High-Risk Diagnoses for the Elderly Scale (HRDES) (16) using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes for discharge diagnoses. The BHCS administrative data include up to 30 discharge diagnoses.

The Elixhauser comorbidity measure, based on the Charlson comorbidity index (13), was developed to predict hospital mortality, charges, and length of stay. The original Elixhauser index has 30 items based on ICD-9-CM diagnosis codes (15) and excludes the primary condition that is the basis of the DRG. We investigated whether the presence of any of the diagnoses in the Elixhauser comorbidity index (primary diagnosis associated with DRG or any comorbid condition) predicted readmission by removing the DRG exclusion criteria from the Elixhauser algorithm. The HRDES was developed to predict 1-year mortality in elders admitted to the general medical service of an acute care hospital (16). This index uses 10 conditions selected from a candidate list of 22 ICD-9-CM–coded conditions. Comorbidity was also analyzed using a single comorbidity covariate consisting of patients' total number of Elixhauser comorbidity categories or the total number of HRDES comorbidity categories.

The geographic variables were defined as the median income in the ZIP code of residence (from Census 2000) and the distance from the centroid of the patient's ZIP code of residence to the centroid of the index hospital's ZIP code. The distances between centroids were calculated using spherical trigonometry (24) and dichotomized at 50 miles, the 90th percentile of distance from the hospital.

All classes of covariates were evaluated for missing data, the magnitude of relative risk (RR) and risk difference in predicting readmission, statistical significance, and overall contribution to the prediction models.

Modeling strategy

The analytic sample was randomly split into a two-thirds derivation cohort (n = 19,528) and a one-third validation cohort (n = 9764). The outcome of hospital readmission within 30 days was analyzed using logistic regression to select covariates and to estimate model discrimination and calibration. Initially, models were constructed using forward addition for each class of covariates to evaluate the additional contribution from health system covariates, comorbidity covariates, and geographic covariates to the model. Models including all of the covariates were further analyzed using backward elimination to identify a parsimonious set of covariates significant at the $P < 0.05$ level. Separate analyses were conducted for the Elixhauser and HRDES comorbidity covariates.

The measures reported for each covariate included unadjusted bivariate RR, adjusted multivariable RR, and adjusted multivariable risk difference. Discrimination between readmitted and non-readmitted patients was evaluated using the C statistic (25). Calibration of the model was evaluated by the Hosmer-Lemeshow statistic (26). Prediction models for 30-day readmission were developed from the analyses using the two-thirds derivation cohort, and the performance of the models from the derivation cohort was evaluated in the one-third validation cohort. Generalized linear modeling was used to calculate the adjusted RR (27) and adjusted absolute risk difference for the variables that were statistically significant in the logistic regression analyses.

Table 1. Characteristics of elders admitted to Baylor Health Care System hospitals and risk of 30-day hospital readmission (N = 29,292)

Characteristics	Prevalence No. (%)	30-day readmission No. (%)	Relative risk (95% CI)
Demographic characteristics			
Age group, y			
65–69	7100 (24.2)	665 (9.4)	1.0
70–74	6491 (22.2)	676 (10.4)	1.11 (1.00, 1.23)
75–79	6291 (21.5)	794 (12.6)	1.35 (1.22, 1.49)
80–84	4944 (16.9)	649 (13.1)	1.40 (1.27, 1.55)
85+	4466 (15.3)	648 (14.5)	1.55 (1.40, 1.71)
Sex			
Female	16,831 (57.5)	1914 (11.4)	1.0
Male	12,461 (42.5)	1518 (12.2)	1.07 (1.01, 1.14)
Race			
White	24,006 (82.0)	2769 (11.5)	1.0
African American	3051 (10.4)	436 (14.3)	1.24 (1.13, 1.36)
Other	2235 (7.6)	227 (10.2)	0.88 (0.77, 1.00)
Insurance			
Medicare only	4266 (14.6)	636 (14.9)	1.0
Medicare and Medicaid	2767 (9.5)	342 (12.4)	0.83 (0.73, 0.94)
Medicare and other	20,250 (69.1)	2283 (11.3)	0.76 (0.70, 0.82)
Other	2009 (6.9)	171 (8.51)	0.57 (0.49, 0.67)
Services			
Medicine	21,365 (72.9)	2738 (12.8)	1.0
Surgery	7927 (27.1)	694 (8.75)	0.68 (0.63, 0.74)
Discharge			
Home	21,163 (72.3)	2025 (9.6)	1.0
Home care	3540 (12.1)	378 (10.7)	1.12 (1.01, 1.24)
Long-term care	4589 (15.7)	1029 (22.4)	2.34 (2.19, 2.51)
Distance (N = 29,199)			
<50 mi	26,046 (89.2)	3157 (12.1)	1.0
≥50 mi	3153 (10.8)	265 (8.4)	0.69 (0.62, 0.78)
Income quartiles (N = 28,120)			
<$34,295	7092 (25.2)	862 (12.2)	1.0
$34,295–$43,294	7124 (25.3)	801 (11.2)	0.95 (0.88, 1.02)
$43,295–$51,074	6892 (24.5)	897 (13.0)	1.15 (1.07, 1.23)
≥$51,075	7012 (24.9)	767 (10.9)	0.91 (0.85, 0.99)
Elixhauser comorbidity variables			
Alcohol abuse	348 (1.2)	43 (12.4)	1.06 (0.80, 1.40)
Deficiency anemia	4863 (16.6)	835 (17.2)	1.62 (1.50, 1.74)
Rheumatoid arthritis/collagen vascular disease	780 (2.7)	118 (15.1)	1.30 (1.10, 1.54)
Chronic blood loss anemia	517 (1.8)	70 (13.5)	1.16 (0.93, 1.44)
Congestive heart failure	5789 (19.8)	948 (16.4)	1.55 (1.45, 1.66)
Chronic pulmonary disease	6151 (21.0)	860 (14.0)	1.26 (1.17, 1.35)
Coagulopathy	1007 (3.4)	192 (19.1)	1.66 (1.46, 1.90)
Depression	2095 (7.2)	301 (14.4)	1.25 (1.12, 1.39)
Diabetes without chronic complications	5835 (19.9)	765 (13.1)	1.15 (1.07, 1.24)
Diabetes with chronic complications	1059 (3.6)	184 (17.4)	1.51 (1.32, 1.73)
Drug abuse	70 (0.24)	12 (17.1)	1.46 (0.87, 2.45)
Hypertension with complications	17,317 (59.1)	1923 (11.1)	0.88 (0.83, 0.94)
Hypothyroidism	4295 (14.7)	539 (12.6)	1.08 (0.99, 1.18)
Liver disease	485 (1.7)	86 (17.7)	1.53 (1.26, 1.85)
Lymphoma	375 (1.3)	74 (19.7)	1.70 (1.38, 2.09)
Fluid and electrolyte disorders	8242 (28.1)	1306 (15.9)	1.57 (1.47, 1.67)
Metastatic cancer	1259 (4.3)	214 (17.0)	1.48 (1.31, 1.68)
Obesity	1325 (4.5)	145 (10.9)	0.93 (0.80, 1.09)
Other neurological disorders	2552 (8.7)	374 (14.7)	1.28 (1.16, 1.42)
Paralysis	825 (2.8)	172 (20.9)	1.82 (1.59, 2.09)
Peripheral vascular disease	2916 (10.0)	452 (15.5)	1.37 (1.25, 1.50)
Psychoses	707 (2.4)	99 (14.0)	1.20 (1.00, 1.45)
Pulmonary circulation disease	692 (2.4)	117 (16.9)	1.46 (1.23, 1.73)
Renal failure	932 (3.2)	201 (21.6)	1.89 (1.67, 2.15)
Solid tumor without metastasis	2833 (9.7)	396 (14.0)	1.22 (1.11, 1.34)
Peptic ulcer disease and bleeding	30 (0.1)	2 (6.7)	0.57 (0.15, 2.17)
Valvular disease	2258 (7.7)	303 (13.4)	1.16 (1.04, 1.29)
Weight loss	890 (3.0)	188 (21.1)	1.85 (1.62, 2.11)
HRDES comorbidity variables			
Bone marrow failure	504 (1.7)	79 (15.7)	1.35 (1.10, 1.65)
Cancer (metastatic)	1213 (4.1)	206 (17.0)	1.48 (1.30, 1.68)
Cancer (solid tumor localized)	2903 (9.9)	407 (14.0)	1.22 (1.11, 1.35)
Cirrhosis/end-stage liver disease	345 (1.2)	72 (20.9)	1.80 (1.46, 2.21)
Congestive heart failure	5922 (20.2)	951 (16.1)	1.51 (1.41, 1.62)
Decubitus ulcer	370 (1.3)	77 (20.8)	1.79 (1.47, 2.19)
Delirium	778 (2.7)	132 (17.0)	1.47 (1.25, 1.72)
Dementia	1425 (4.9)	183 (12.8)	1.10 (0.96, 1.27)
Lymphoma/leukemia	440 (1.5)	86 (19.5)	1.69 (1.39, 2.04)
Major depression	2024 (6.9)	296 (14.6)	1.27 (1.14, 1.42)
Malnutrition/weight loss	913 (3.1)	204 (22.3)	1.96 (1.73, 2.23)
Renal failure/acute	1158 (4.0)	254 (21.9)	1.94 (1.73, 2.18)
Renal failure/chronic	590 (2.0)	115 (19.5)	1.69 (1.43, 1.99)
Respiratory failure	1069 (3.6)	233 (21.8)	1.92 (1.71, 2.16)
COPD/chronic lung disease	4683 (16.0)	685 (14.6)	1.31 (1.21, 1.42)
Sepsis	978 (3.3)	193 (19.7)	1.73 (1.51, 1.97)
Diabetes mellitus	920 (3.1)	159 (17.3)	1.50 (1.30, 1.73)
Major stroke/hemiplegia	882 (3.0)	170 (19.3)	1.68 (1.46, 1.93)
Multiple trauma/fractures	638 (2.2)	92 (14.4)	1.24 (1.02, 1.50)
Myocardial infarction	1377 (4.7)	199 (14.5)	1.25 (1.09, 1.42)
Pneumonia	2423 (8.3)	398 (16.4)	1.45 (1.32, 1.60)
Severe peripheral vascular disease	327 (1.1)	70 (21.4)	1.84 (1.49, 2.28)

CI indicates confidence interval; HRDES, High-Risk Diagnoses in the Elderly Scale; COPD, chronic obstructive pulmonary disease.

In the final analysis, the model with the significant demographic, health system, and Elixhauser comorbidity variables and the model with the significant demographic, health system, and HRDES variables were evaluated in the full 2-year cohort, and the population-attributable risk (PAR) was calculated. The PAR was calculated using the prevalence of each factor and the adjusted RR from the multivariate analyses to identify priority conditions for hospital discharge programs to reduce 30-day readmission. Analyses were performed using SAS 9.1 (SAS Institute Inc, Cary, NC) and STATA 8.2 (StataCorp LP, College Station, TX). A *P* value <0.05 was considered statistically significant.

RESULTS

Unadjusted analyses

In the overall cohort *(Table 1)*, there were 3432 (11.72%) readmissions to BHCS hospitals within 30 days of discharge. Age >75 years, African American race, Medicare health insurance with no other health insurance, medical service, discharge to home with home care or discharge to long-term care, residence within 50 miles of the index hospital, and only the third quartile of median income were significant univariate predictors for 30-day readmission.

Multivariable analyses of independent predictors of 30-day readmission

In the analysis with the Elixhauser comorbidity variables, age >75 years, male sex, and African American race were independently associated with higher risk of 30-day hospital readmission. Patients discharged to either a skilled nursing facility or a long-term care facility had a twofold risk of 30-day hospital readmission, corresponding to a 10 percentage point increase in the probability of 30-day readmission. Surgical service patients had a lower risk of readmission (RR, 0.85), corresponding to a 1.3 percentage point lower probability of 30-day readmission. The demographic and health system variables had similar RR and risk difference in the analyses with the Elixhauser comorbidity variables *(Table 2)* and the HRDES comorbidity variables *(Table 3)*.

Table 2. Risk factors for 30-day hospital readmission in the derivation cohort according to Elixhauser comorbidity variables

	Derivation cohort (N = 19,528)	
Characteristics	Relative risk (95% CI)	Risk difference (95% CI)
Demographic characteristics		
Age group, y		
65–69	1.00	0.000
70–74	1.11 (0.98, 1.26)	.012 (.001, .023)
75–79	1.28 (1.14, 1.44)	.027 (.015, .039)
80–84	1.19 (1.05, 1.36)	.021 (.008, .034)
85+	1.27 (1.12, 1.46)	.033 (.018, .047)
Male	1.14 (1.05, 1.23)	.008 (.000, .017)
African American	1.14 (1.02, 1.28)	.010 (–.005, .025)
Health system variables		
Long-term care	2.00 (1.82, 2.19)	.104 (.088, .121)
Medicare and Medicaid	0.79 (0.70, 0.90)	–.015 (–.029, –.002)
Non-Medicare	0.72 (0.60, 0.86)	–.019 (–.032, –.005)
Surgery service	0.85 (0.77, 0.94)	–.013 (–.022, –.004)
Comorbidity variables*		
Lymphoma	1.53 (1.16, 2.00)	.069 (.021, .116)
Metastatic cancer	1.38 (1.15, 1.67)	.041 (.014, .068)
Renal failure	1.35 (1.13, 1.61)	.068 (.035, .101)
Paralysis	1.33 (1.11, 1.58)	.050 (.018, .081)
Diabetes with chronic complications	1.32 (1.11, 1.56)	.042 (.014, .071)
Liver disease	1.30 (1.03, 1.65)	.038 (–.002, .079)
Weight loss	1.30 (1.11, 1.52)	.052 (.018, .086)
Coagulopathy	1.30 (1.12, 1.51)	.046 (.016, .075)
Congestive heart failure	1.30 (1.19, 1.41)	.034 (.021, .047)
Peripheral vascular disease	1.28 (1.14, 1.43)	.032 (.016, .047)
Rheumatoid arthritis/collagen vascular disease	1.23 (1.00, 1.52)	.026 (–.001, .054)
Solid tumor without metastasis	1.22 (1.05, 1.42)	.028 (.012, .046)
Deficiency anemia	1.20 (1.09, 1.31)	.021 (.008, .035)
Fluid and electrolyte disorders	1.16 (1.07, 1.27)	.018 (.007, .028)
Diabetes without chronic complications	1.13 (1.03, 1.25)	.017 (.006, .028)
Chronic pulmonary disease	1.12 (1.03, 1.23)	.013 (.002, .024)
Hypertension with complications	0.89 (0.83, 0.97)	–.011 (–.020, –.003)
Constant	—	.058 (.037, .079)

*Comorbidity variables reported in descending order by relative risk.
CI indicates confidence interval.

The Elixhauser comorbidity variables significantly associated with an increased risk of 30-day readmission included conditions affecting major organ systems (lymphoma, metastatic cancer, renal failure, paralysis, diabetes with chronic complications, liver disease, congestive heart failure, peripheral vascular disease, rheumatoid arthritis/collagen vascular disease, solid tumor without metastases, diabetes without chronic complications, and chronic pulmonary disease) and systemic conditions (coagulopathy, weight loss, deficiency anemia, and fluid and electrolyte disorders) (Table 2). The magnitude of increased risk of 30-day readmission was similar for most of the comorbid conditions, with RR ranging from 1.12 to 1.53, corresponding to a 1.3 to 6.9 percentage point increase in the probability of 30-day readmission. Hypertension with complications was the only condition associated with a decreased risk of 30-day readmission (RR, 0.89; 95% confidence interval [CI], 0.83–0.97).

The HRDES comorbidity variables significantly associated with an increased risk of 30-day hospital readmission included diseases affecting the major organ systems (peripheral vascular disease, lymphoma/leukemia, cirrhosis/end-stage liver disease,

Table 3. Risk factors for 30-day hospital readmission in the derivation cohort according to HRDES comorbidity variables

Characteristics	Derivation cohort (N = 19,528) Relative risk (95% CI)	Risk difference (95% CI)
Demographic characteristics		
Age group, y		
65–69	1.00	0.000
70–74	1.11 (1.00, 1.26)	.010 (–.001, .021)
75–79	1.30 (1.15, 1.46)	.027 (.015, .039)
80–84	1.22 (1.08, 1.39)	.023 (.010, .036)
85+	1.28 (1.13, 1.47)	.033 (.018, .048)
Male	1.13 (1.05, 1.23)	.008 (–.000, .016)
African American	1.18 (1.06, 1.32)	.013 (–.003, .028)
Health system variables		
Long-term care	2.05 (1.87, 2.26)	.105 (.088, .121)
Medicare and Medicaid	0.83 (0.73, 0.95)	–.009 (–.023, .005)
Non-Medicare	0.70 (0.58, 0.84)	–.024 (–.038, –.010)
Surgery service	0.80 (0.73, 0.89)	–.018 (–.027, –.009)
Comorbidity variables*		
Severe peripheral vascular disease	1.77 (1.42, 2.21)	.091 (.036, .145)
Lymphoma/leukemia	1.76 (1.39, 2.25)	.093 (.049, .138)
Cirrhosis/end-stage liver disease	1.52 (1.17, 1.97)	.072 (.021, .123)
Renal failure (chronic)	1.50 (1.22, 1.85)	.079 (.040, .119)
Major stroke (hemiplegia)	1.42 (1.19, 1.68)	.052 (.020, .084)
Cancer (metastatic)	1.41 (1.17, 1.71)	.046 (.019, .073)
Malnutrition/weight loss	1.40 (1.20, 1.63)	.074 (.040, .108)
Respiratory failure	1.37 (1.18, 1.58)	.047 (.015, .078)
Congestive heart failure	1.34 (1.23, 1.46)	.038 (.026, .051)
Renal failure (acute)	1.25 (1.08, 1.45)	.053 (.024, .082)
Cancer (solid tumor, localized)	1.22 (1.05, 1.41)	.026 (.010, .043)
COPD/chronic lung disease	1.11 (1.00, 1.22)	.017 (.004, .029)
Dementia	0.81 (0.69, 0.97)	–.016 (–.036, .004)
Constant	—	.070 (.051, .090)

*Comorbidity variables reported in descending order by relative risk.
HRDES indicates High-Risk Diagnoses in the Elderly Scale; CI, confidence interval; COPD, chronic obstructive pulmonary disease.

chronic renal failure, stroke, metastatic cancer, respiratory failure, congestive heart failure, acute renal failure, localized cancer, and chronic obstructive pulmonary disease/chronic lung disease) and only one systemic condition, malnutrition/unexplained weight loss. The magnitude of increased risk of 30-day readmission for most of these conditions was similar to the risk of the corresponding Elixhauser comorbidity covariates, with RR ranging from 1.11 to 1.77, corresponding to a 1.7 to 9.1 percentage point increase in risk (Table 3). Dementia was the only condition associated with a significantly lower risk of 30-day readmission (RR, 0.81; 95% CI, 0.69–0.97).

In preliminary analyses, patients residing >50 miles from the initial admission hospital had a significantly lower risk of 30-day readmission. A restricted sample of elders from the derivation cohort (n = 17,364) residing within 50 miles of the index hospital was compared with the derivation cohort regarding residence information. These two analyses identified the same covariates, had essentially the same discrimination (C statistic, 0.649 and 0.654, respectively), and adequate calibration ($\chi^2 = 10.43$, $P > 0.24$ vs $\chi^2 = 6.35$, $P > 0.61$). Median income was not significantly associated with 30-day readmission. The final models omitted the geographic variables because of concerns about ascertaining readmissions to hospitals outside of BHCS and because missing geographic data would limit the reproducibility of estimates of readmission risk related to patient distance from the hospital.

Validation of the prediction models for 30-day readmission

The models for 30-day readmission in the derivation cohort using the identified Elixhauser or HRDES comorbidity variables had equally good discrimination in the derivation

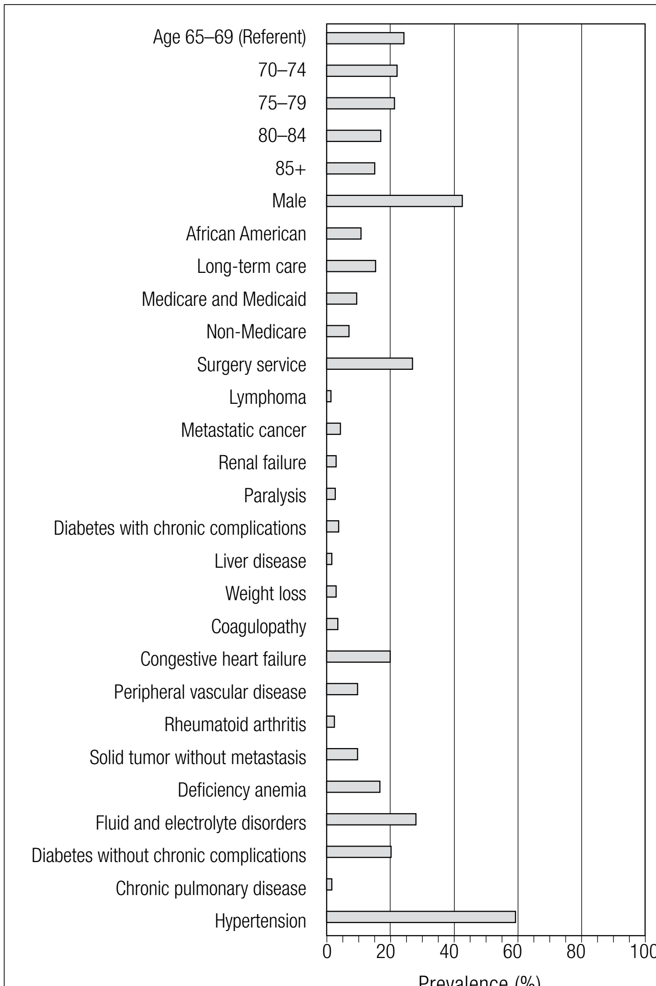

Figure 1. Prevalence of risk factors for 30-day hospital readmission. The prevalence of the significant demographic, health system, and Elixhauser comorbidity predictors of 30-day hospital readmission among the 29,292 eligible elders admitted to the seven BHCS hospitals from July 2002 to June 2004 is shown.

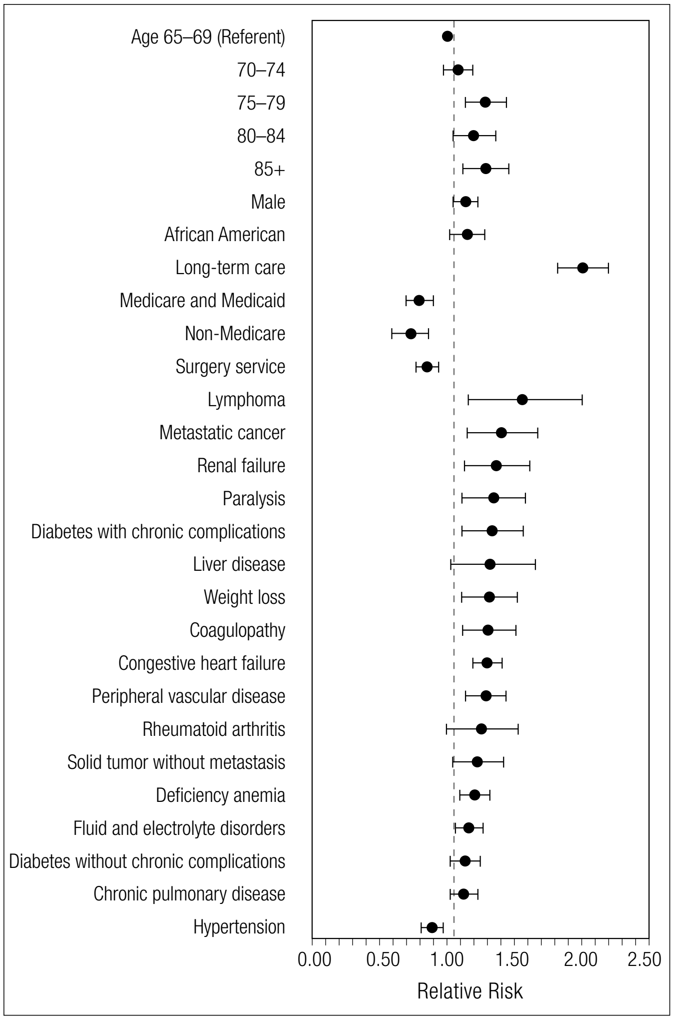

Figure 2. Relative risk of 30-day hospital readmission. The relative risk and 95% confidence intervals for the significant demographic, health system, and Elixhauser comorbidity predictors of 30-day hospital readmission among the 29,292 eligible elders admitted to the seven BHCS hospitals from July 2002 to June 2004 are shown.

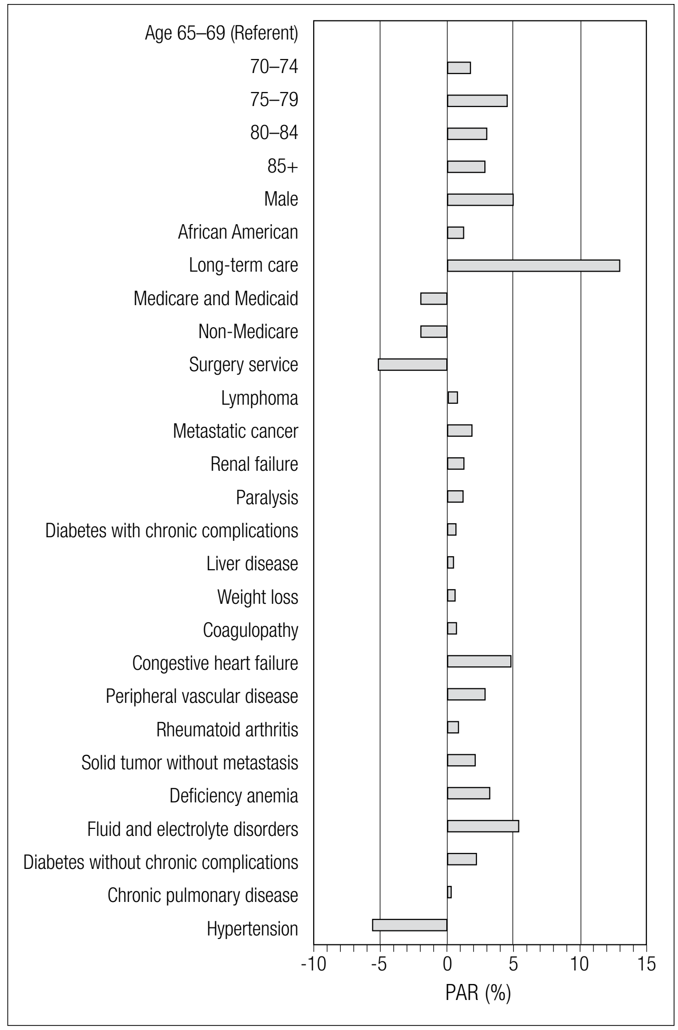

Figure 3. Population-attributable risk (PAR) of 30-day hospital readmission. The population-attributable risk of the significant demographic, health system, and Elixhauser comorbidity predictors of 30-day hospital readmission among the 29,292 eligible elders admitted to the seven BHCS hospitals from July 2002 to June 2004 is shown. Among these elders, dual Medicare and Medicaid insurance, no Medicare insurance coverage, admission to a surgical service, or hypertension with complications as a comorbidity were associated with a significantly lower risk of 30-day hospital admission.

and validation cohorts (C statistic, 0.65 and 0.63, respectively, for models using Elixhauser comorbidity and 0.65 and 0.63, respectively, for models using HRDES comorbidity); likewise for calibration (χ^2 = 6.08, P = 0.64 vs χ^2 = 12.53, P = 0.25 for models with Elixhauser comorbidity classification, and χ^2 = 10.43, P = 0.26 vs χ^2 = 17.02, P = 0.07 for models with HRDES comorbidity classification).

Threshold for predicting 30-day readmission

As the cutoff threshold for predicting 30-day readmission increased, the proportion of patients identified as having a high risk of 30-day readmission decreased, but the proportion of correct predictions (positive predictive value) increased. In the Elixhauser major comorbidity model, a 25% threshold probability for predicting 30-day readmission identified 4.1% of the admitted elders as having high risk of 30-day readmission, and 31% of these were readmitted within 30 days. A threshold probability of 30% identified 1.4% of the admitted elders as having high risk, and 34% of these were readmitted within 30 days.

Models with counts of comorbid conditions

Models that included the demographic and health system variables and a single comorbidity variable consisting of a total count of the number of either Elixhauser or HRDES comorbid conditions (equal weight for each comorbid condition) performed almost as well as models with individual indicators for the comorbid conditions (C statistic = 0.636, χ^2 = 12.09, P = 0.15 for Elixhauser comorbid conditions, and C statistic = 0.647, χ^2 = 10.07, P = 0.26 for HRDES comorbid conditions). Each Elixhauser comorbid condition had an RR of 1.12 (95% CI, 1.1–1.15) in the probability of 30-day readmission, corresponding to a 1.3 percentage point increase in the probability of 30-day readmission. Each HRDES comorbid condition had an RR of 1.18 (95% CI, 1.15–1.22) in the probability of 30-day readmission, corresponding to a 2.6 percentage point increase (95% CI, 2.26–2.97) in the probability of 30-day readmission.

Table 4. Population-attributable risk of 30-day hospital readmission in a cohort of elders according to Elixhauser comorbidity variables (N = 29,292)

Characteristics	Prevalence (%)	Relative risk (95% CI)	Population-attributable risk (%)
Demographic characteristics			
Age group, y			
65–69	24.2	1.00	0
70–74	22.2	1.08 (0.98, 1.19)	1.74
75–79	21.5	1.22 (1.11, 1.34)	4.52
80–84	16.9	1.18 (1.07, 1.31)	2.95
85+	15.3	1.19 (1.06, 1.32)	2.82
Male	42.5	1.12 (1.05, 1.19)	4.85
African American	10.4	1.13 (1.02, 1.24)	1.33
Health system variables			
Long-term care	15.7	1.94 (1.80, 2.09)	12.86
Medicare and Medicaid	9.5	0.79 (0.71, 0.88)	–2.04
Non-Medicare	6.9	0.72 (0.62, 0.83)	–1.97
Surgery service	27.1	0.82 (0.75, 0.89)	–5.13
Comorbidity variables*			
Fluid and electrolyte disorders	28.1	1.20 (1.12, 1.28)	5.32
Congestive heart failure	19.8	1.25 (1.17, 1.35)	4.72
Deficiency anemia	16.6	1.20 (1.12, 1.30)	3.21
Peripheral vascular disease	10.0	1.29 (1.17, 1.41)	2.82
Diabetes without chronic complications	19.9	1.11 (1.03, 1.20)	2.14
Solid tumor without metastasis	9.7	1.22 (1.08, 1.37)	2.09
Metastatic cancer	4.3	1.44 (1.23, 1.68)	1.86
Renal failure	3.2	1.40 (1.22, 1.62)	1.26
Paralysis	2.8	1.43 (1.25, 1.64)	1.19
Rheumatoid arthritis/collagen vascular disease	2.7	1.32 (1.12, 1.56)	0.86
Lymphoma	1.3	1.65 (1.34, 2.04)	0.84
Coagulopathy	3.4	1.21 (1.06, 1.38)	0.71
Diabetes with chronic complications	3.6	1.18 (1.03, 1.37)	0.64
Weight loss	3.0	1.19 (1.04, 1.36)	0.57
Liver disease	1.7	1.31 (1.08, 1.59)	0.52
Chronic pulmonary disease	1.8	1.16 (1.08, 1.25)	0.29
Hypertension	59.1	0.91 (0.85, 0.97)	–5.62

*Comorbidity variables reported in descending order of population-attributable risk.
CI indicates confidence interval.

Population-attributable risk of 30-day readmission

The prevalence, relative risk, and population-attributable risk of the significant demographic, health system, and Elixhauser comorbidity risk factors for 30-day hospital readmission are shown in *Figures 1–3.* In the analysis using the Elixhauser comorbidity variables *(Table 4),* elders discharged to long-term care had the highest PAR (12.86%) for a 30-day readmission. The group aged 75 to 79 had the highest PAR (4.52%). Other high-risk groups based on PAR for 30-day readmission were men (4.85%) and African Americans (1.33%).

In the same analysis, the nine conditions with a PAR ≥1% were fluid and electrolyte disorders (5.32%), congestive heart failure (4.72%), deficiency anemia (3.21%), peripheral vascular disease (2.82%), diabetes without chronic complications (2.14%), solid tumor without metastases (2.09%), metastatic cancer (1.86%), renal failure (1.26%), and paralysis (1.19%)

In the analysis using the HRDES comorbidity variables *(Table 5),* the 10 conditions with a PAR ≥1% were congestive heart failure (5.18%), localized cancer/solid tumor (2.04%), chronic obstructive pulmonary disease/chronic lung disease (2.04%), metastatic cancer (1.87%), malnutrition/weight loss (1.81%), major stroke/hemiplegia (1.66%), acute renal failure (1.25%), severe peripheral vascular disease (1.22%), respiratory failure (1.12%), and lymphoma/leukemia (1.08%).

DISCUSSION

We used readily available demographic, health system, and clinical comorbidity data to develop and validate a model to predict 30-day hospital readmission for elders admitted to medical or surgical services of acute care hospitals. We found that older age, male sex, African American race, Medicare-only insurance without supplemental health insurance, medical service admission, and discharge to long-term care were independently associated with increased risk of 30-day hospital readmission. Major comorbid conditions similarly predicted 30-day readmission using either the Elixhauser or the HRDES classification. The highest PAR for 30-day hospital admission was due to discharge to long-term care. High-priority conditions for interventions to reduce 30-day readmission can be identified using either the Elixhauser or HRDES classifications. The specific magnitude of risk and rank order of the PAR for individual categories differ between the two classifications, resulting in part from the specific ICD-9-CM codes included in each category and in part from the inclusion of systemic condition categories, such as fluid and electrolyte disorders, which are associated with other disease categories.

The Elixhauser comorbidity index was designed to assess the impact of comorbid conditions on outcomes independent of the diagnoses explaining the hospital admission (DRG) (15). In a separate analysis of predictors of 30-day readmission, models with Elixhauser categories based on primary and comorbid diagnoses (implemented by removing the DRG exclusion from the Elixhauser algorithm) had similar discrimination as models with the comorbidity and DRG exclusion (receiver operating characteristic curve area, 0.65 vs 0.63).

Predictive models for 30-day readmission based on demographic variables (age, sex, and race), health system variables (health insurance, hospital service, and discharge location),

Table 5. Population-attributable risk of 30-day hospital readmission in a cohort of elders according to HRDES comorbidity variables (N = 29,292)

Characteristics	Prevalence (%)	Relative risk (95% CI)	Population-attributable risk (%)
Demographic characteristics			
Age group, y			
65–69	24.2	1.00	0
70–74	22.2	1.08 (0.97, 1.19)	1.74
75–79	21.5	1.23 (1.11, 1.35)	4.71
80–84	16.9	1.20 (1.08, 1.34)	3.27
85+	15.3	1.20 (1.07, 1.34)	2.95
Male	42.5	1.11 (1.04, 1.18)	4.47
African American	10.4	1.19 (1.08, 1.30)	1.94
Health system variables			
Long-term care	15.7	2.05 (1.89, 2.21)	14.15
Medicare and Medicaid	9.5	0.81 (0.73, 0.91)	–1.82
Non-Medicare	6.9	0.70 (0.61, 0.82)	–2.03
Surgery service	27.1	0.77 (0.71, 0.84)	–6.65
Comorbidity variables*			
Congestive heart failure	20.2	1.27 (1.17, 1.36)	5.18
Cancer (solid tumor, localized)	9.9	1.21 (1.07, 1.36)	2.04
COPD/chronic lung disease	16.0	1.16 (1.07, 1.26)	2.04
Cancer (metastatic)	4.1	1.46 (1.25, 1.71)	1.87
Malnutrition/weight loss	3.1	1.28 (1.13, 1.46)	1.81
Major stroke (hemiplegia)	3.0	1.41 (1.23, 1.62)	1.66
Renal failure (acute)	4.0	1.32 (1.17, 1.49)	1.25
Severe peripheral vascular disease	1.1	1.57 (1.28, 1.93)	1.22
Respiratory failure	3.6	1.31 (1.16, 1.48)	1.12
Lymphoma/leukemia	1.5	1.73 (1.42, 2.11)	1.08
Renal failure (chronic)	2.0	1.41 (1.18, 1.68)	0.82
Cirrhosis/end-stage liver disease	1.2	1.53 (1.24, 1.89)	0.62
Dementia	4.9	0.77 (0.66, 0.89)	–1.15

*Comorbidity variables reported in descending order of population-attributable risk.
HRDES indicates High-Risk Diagnoses in the Elderly Scale; CI, confidence interval; COPD, chronic obstructive pulmonary disease.

and either 10 Elixhauser major comorbidity categories or 13 HRDES comorbidity categories were valid predictors of early (30-day) hospital readmission. Alternatively, models based on demographic variables, health system variables, and the total count of either the number of Elixhauser comorbidity categories or HRDES comorbidity categories were also valid predictors of 30-day hospital readmission.

For each model the probability of readmission can be easily obtained by summing the baseline 30-day readmission probability and the covariate-specific incremental probabilities (risk differences). For example, using the risk difference estimates for the Elixhauser comorbidity in Table 2, the probability of 30-day hospital readmission for a 78-year-old African American man with Medicare insurance admitted to a medical service for heart failure and diabetes mellitus without chronic complications would be 0.154, or 15.4%. This is calculated as the sum of the baseline risk (0.058) and the age category risk (0.027), male sex (0.008), African American race (0.010), Medicare insurance referent category risk (0), medical service referent category risk (0), Elixhauser comorbidity category risk for congestive heart failure (0.034), and diabetes mellitus without chronic complications (0.017).

The predictive models for 30-day hospital readmission may be most useful in two areas. First, the probability of readmission can be used early during the patient's hospital admission to estimate the risk of hospital readmission and identify elders who may benefit from more coordinated care management, intensive assessment, and additional services after hospital discharge. An elder's demographic characteristics (age, sex, race, health insurance, and anticipated discharge location) and major diagnoses are likely to be known in the first day or two after admission, and elders at risk of readmission can be identified at the time of discharge planning. Second, to reduce elders' risk of hospital readmission, hospital administrators and others responsible for discharge planning and care coordination programs can use the PAR in setting priorities for allocating personnel and resources to discharge planning and postdischarge care programs. Our results suggest that interventions in the long-term care setting may be effective in reducing hospital readmissions. Patients with cardiovascular disease (heart failure and peripheral vascular disease), chronic lung disease, renal failure, cancer, and diabetes mellitus were identified as having a high PAR of readmission. Previous studies have shown that patient interventions for heart failure reduce hospital readmissions (28–30).

Previous studies of hospital readmission in the Medicare population found that male sex, Medicaid insurance, prior admission, and admission to hospitals with fewer beds were significantly associated with a higher risk of 60-day readmission, while younger age, nonwhite race, self-limited disease, surgery performed, and urban hospitals were associated with a lower risk of 60-day readmission (4). Our study contained more detailed comorbidity and discharge location information and found a similar relationship for age and a different relationship for African American race. A 1991 meta-analysis of 44 studies reported that diagnoses, age, initial length of hospital stay, and prior use of hospital resources were related to readmission, but the strength of the relationship was trivial (31). In our study, patients discharged to a skilled nursing facility had the highest risk of 30-day readmission. In contrast, a study of elders with chronic obstructive pulmonary disease, stroke, or dementia who were discharged to a nursing home were less likely to be readmitted within 30 days than patients discharged to home (32). Another study of medical patients from a single hospital used recursive partitioning and identified three high-risk diagnoses (AIDS, renal disease, and cancer), albumin level, and prior admission within 60 days as factors associated with 90-day readmission (12). A study of complicated care transitions in elders found that age, sex, insurance, prior hospitalizations, and three specific comorbidities (heart disease, diabetes mellitus, and cancer) predicted complicated transitions and that the predictions improved when information on health status and activities of daily living were included (23). In 2000, a narrative review of hospital readmissions as a measure of quality of care concluded that most readmissions seemed to be caused by modifiable factors and that global readmission rates were not a useful indicator of quality of care. The authors noted, however, that a focus on specific needs of patients with defined problems may identify quality of care problems and lead to the creation of a more responsive health care system for the chronically ill (19). We have developed and validated a method to identify elders at risk of 30-day readmission who may benefit from interventions to reduce readmission.

Our study has several strengths. First, the prediction rule is nonproprietary, and we encourage other investigators to use our prediction models in their settings and replicate our analytic approach with their locally available data. Second, the prediction rules were developed using administrative data readily available in hospital discharge databases. Third, the study included patients in both the medical and surgical services admitted to seven community hospitals of different sizes, including a tertiary care referral hospital. The study findings should therefore generalize to settings outside BHCS. Fourth, our study covers a range of variables in the conceptual domains of predisposing factors, need factors, and enabling factors (33, 34). The covariates available in the hospital administrative data included demographic factors of age, sex, and race which may *predispose* to readmission; clinical conditions and type of hospital service related to the *need* for subsequent inpatient care; health insurance that may *enable* access to care and readmission; discharge with home care or discharge to a skilled nursing facility that may either substitute for inpatient care or facilitate access to subsequent inpatient care; distance, which may be a barrier to readmission or associated with care in a non-BHCS hospital; and income.

Our study was limited by its reliance on readily available hospital administrative data used to classify the DRG of the admission for billing and reimbursement purposes, and we were unable to fully replicate the covariates used in some of the published prediction models for hospital readmission in elders (9–11). Administrative data based on codes from medical record review are known to be less accurate than prospectively collected clinical data and tend to underreport chronic conditions (35–37). We included all readmissions because we were unable to identify planned readmissions, and our estimates may overestimate the risks of unplanned 30-day hospital readmission. We found that patients who resided 50 miles or more from the initial hospital (the top decile of distance) were less likely to be readmitted, which could be due to underascertainment of readmission of these patients to non-BHCS hospitals. However, analyses restricted to patients who resided within 50 miles of the index hospital yielded the same predictors of 30-day readmission, so we believe that these predictors are valid. We also used an ecological variable (median income quartile of ZIP code of residence) as a surrogate for income and other resources (social capital) that may be associated with access to care and hospital readmission. These covariates were not included in the final models because of concern about ascertainment of readmissions, missing ZIP code data, and lack of independent statistical significance for median income of ZIP code of residence.

An important limitation of our study was that it did not directly include information on patients' abilities to perform activities of daily living or other measures of physical function. It should be noted, however, that limitations in activities of daily living are required for eligibility for home care and are associated with admission to skilled nursing facilities, which were included in our analyses. Our index was designed to select patients based on information that would be available soon after an elder's admission. Thus, our predictors did not include measures of patients' stability, such as absence of fever for 48 hours prior to discharge or stable medication regimen in the 48 hours prior to discharge.

We believe that our predictive models will be useful in identifying elders who may benefit from interventions early during their hospital course. This could improve elders' transition from the hospital to home or to a skilled nursing care facility and could assist hospital administrators in setting priorities for allocating resources for care management and discharge planning.

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